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Crop Production, Transport Infrastructure, and Agrobusiness Nexus

Evidence from Madagascar

Atsushi Iimi
Liangzhi You
Ulrike Wood-Sichra

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Abstract

The literature suggests a wide range of impacts of improved transport connectivity on agricultural growth. Still, the infrastructure-growth nexus remains somewhat mysterious, particularly in the African context, because many rural farmers do not have their own transport means. Using data from Madagascar, the paper reexamines the important roles of agrobusinesses. By applying the spatial autoregressive model, it is shown that proximity to input-oriented agrobusinesses, such as input dealers and equipment suppliers, is particularly important to increase rice production. Fertilizer and irrigation use is also found important, indicating the needs for intensification in rice production. Market accessibility is always found as a significant determinant: transport infrastructure connecting farmers and markets, especially the capital city, Antananarivo, is therefore important to develop and maintain.

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Crop Production, Transport Infrastructure, and Agrobusiness Nexus: Evidence from Madagascar

Atsushi Iimi,[1¶] Liangzhi You,[2] Ulrike Wood-Sichra[2]

[1] Transport & Digital Development Global Practice, World Bank

[2] International Food Policy Research Institute (IFPRI)

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[¶] Corresponding author. Atsushi Iimi, Senior Economist, World Bank Group. Tel: 202-473-4698; Email: aiimi@worldbank.org

I. INTRODUCTION

There are a number of studies showing various impacts of improved transport connectivity on economic growth. For example, Lokshin and Yemtsov (2005) and Danida (2010) show that in the short term, people's transport costs and travel time can be reduced by improved road conditions. In the medium term, agricultural productivity is likely be improved (Donaldson, 2010; Dorosh, et al., 2012), with input prices reduced (Khandker et al., 2009) and output prices increased (Bell and Van Dillen, 2012). Firms could also become more productive with more services offered in local economies (Mu and van de Walle, 2011). Then, poverty may be reduced over the long term (Dercon et al., 2008; Khandker and Koolwal, 2011).

Particularly in the African context, transport infrastructure has a lot of roles to contribute to agricultural growth. In the region, access to advanced inputs, such as fertilizer, improved seeds and irrigation, is often found to be a critical constraint (e.g., Gyimah-Brempong, 1987; Bravo-Ortega and Lederman, 2004; Xu et al., 2009). Damania et al. (2017) show that many farmers do not adopt new technologies because of limited transport connectivity. Good transport connectivity motivates farmers to participate in the market transaction (e.g., Rutto et al., 2012; Okay et al., 2016).

Still, the results chain from transport infrastructure to agricultural growth remains somewhat mysterious, particularly in Africa. One of the missing important elements may be agrobusinesses, such as input suppliers, collectors, processors and exporters. In Africa, the vast majority of rural farmers, who engage in subsistence farming, are poor and do not have their own transport means. In addition, affordable transport services are often not available (Teravaninthorn and Raballand, 2009). Therefore, transportation services must of necessity be provided by agribusinesses or trucking companies, for farmers to purchase advanced inputs, such as fertilizer and improved seeds, and access the output market to sell harvested crops. Rashid et al. (2013) show that in Ethiopia, transport costs account for 64-80 percent of fertilizer farmgate prices.

The current paper casts light on agrobusinesses. The roles of input- and output-oriented agrobusinesses may be different. While input prices are likely to be reduced by improved transport infrastructure (Khandker et al., 2009), output prices can either increase (Khandker et al., 2009) or decline (Shively and Thapa, 2016). This may indicate a particular challenge for farmers to take advantage of accessibility to output markets. Even though transport infrastructure is improved, good market opportunities may not be available. Some studies suggest the importance of access to information and communication technology to obtain market information (Zanello 2012; Kiiza and Pederson, 2012). Clearly, agrobusinesses can play an important role to commercialize agricultural produce. In Madagascar, rice productivity is highly correlated with the presence of agrobusinesses even in a simple correlation diagram with district-level data (**Figure 1**).

Figure 1. Correlation between rice productivity and agrobusiness presence

Source: World Bank estimate based on government data.

The paper distinguishes input- and output-oriented agrobusinesses and examines their relative importance for farmers. Despite the relatively rich literature, there are only a few studies that compare the possible impacts of transport accessibility to input and output markets systematically. Negatu and Roth (2002) indicate that transport infrastructure is critical for output commercialization, but not for utilization of fertilizer in northern Ethiopia. Other institutional factors, such as plot size and access to credit, are more important constraints. Data availability is of course a challenge. The paper combines various spatial data and develops different indicators representing the economic proximity of farmers to input- and output-oriented agrobusinesses, using the case of Madagascar.

The remaining sections are organized as follows: Section II develops our empirical strategy and describes our data, including key transport connectivity variables. Section III discusses the main estimation results and some policy implications. Then, Section IV concludes.

II. EMPIRICAL MODEL AND DATA

Following the literature (e.g., Gyimah-Brempong, 1987; Bravo-Ortega and Lederman, 2004), a simple production function is considered with transport connectivity included as one of the production inputs:

$$\ln Y_i = \beta_0 + \beta_A \ln A_i + \sum_k \beta_k \ln X_{ki} + \sum_h \gamma_h \ln Z_{hi} + u_i \qquad (1)$$

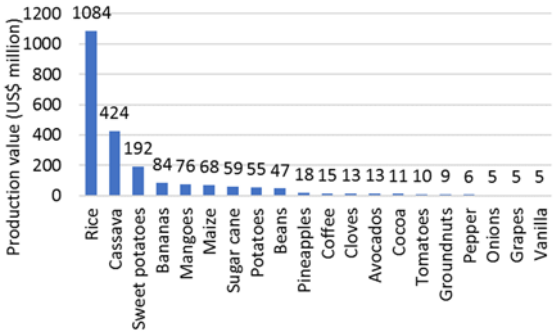
where Y is the volume of rice produced in location i.

Our primary source of data is the spatial production allocation model (SPAM) developed by the International Food Policy Research Institute (IFPRI) for generating geographically highly disaggregated crop production data.[1] The SPAM is a spatial model to allocate crop production derived from large statistics reporting units, such as country, province and district, to a raster grid at a spatial resolution of 5 minutes of arc (approximately, at a resolution of 10km x10km pixel). See You and Wood (2006) and You *et al.* (2009) for details.

While the model covers 42 crops, the current analysis is only focused on rice, which is the most common and important crop in Madagascar. The country's total rice production amounts to about 4 million tons or US$1 billion per annum (**Figure 2**). About 85 percent of farmers engage in rice production. Using the spatial distribution of rice production based on the 2010 SPAM, the latest district-level rice production data for the period of 2013-15 are disaggregated into 3,198 locations or pixels. This is our dependent variable, Y (**Figure 3**).

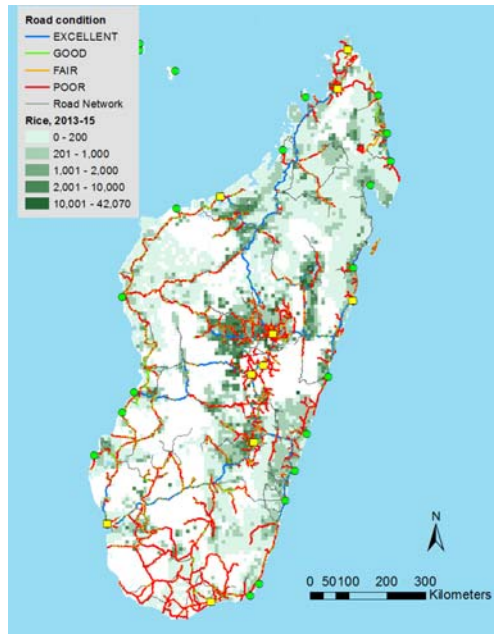
[1] It is available on the Internet at MapSpaM.info.

Figure 2. Madagascar: Main crop production



Source: FOASTAT

Figure 3. Rice production areas



Source: World Bank estimate based on SPAM.

Y is assumed to be dependent on agro-climatic potential A, usual agricultural inputs X as well as transport connectivity Z. Since land fertility differs across locations, it is important to control for crop suitability, A, which represents the amount of rice that can potentially be cultivated at each location (kg/ha).

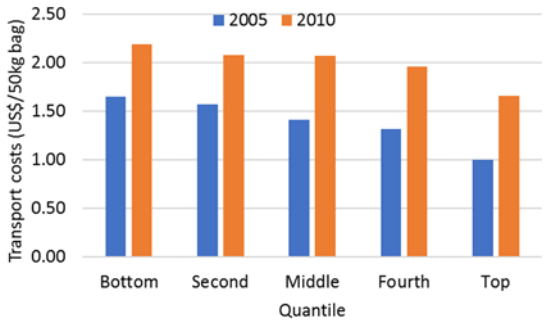
Four traditional production inputs are considered for $X_k = \{L, R, I, F\}$. L denotes labor, which is calculated by the population estimate based on high-resolution global population distribution data, WorldPop, multiplied by the average share of households who engage in agriculture.[2] Land is divided into two types: rain-fed (R) and irrigated (I). F is measured by the total amount of fertilizer. While the land area where high inputs are used is estimated by SPAM, it is assumed that the average dose of fertilizer is 4.5 kg per ha, including all elements of N, P2O5 and K2O (Randrianarisoa et al., 2017). In Africa, agriculture production is generally labor- and land-intensive. The fertilizer and irrigation use remains limited (Bravo-Ortega and Lederman, 2004). However, a growing literature indicates their important

[2] The agricultural employment share is calculated at the district level, using a recent household survey in 2010.

impacts: In Zambia, timely availability of fertilizer could increase maize yields by 11 percent on average (Xu et al., 2009). Improved availability of irrigation could nearly double agricultural productivity in Mali (Dillon, 2011).

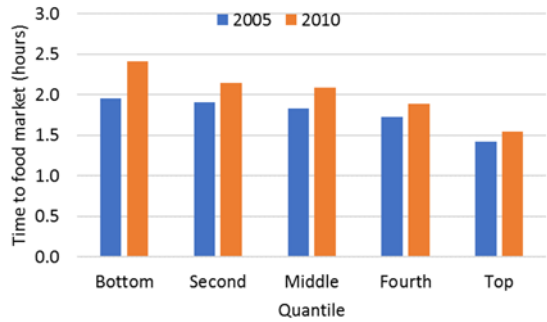
In Madagascar, transport connectivity has long been considered as a critical constraint for rural farmers. World Bank (2016) identifies two important factors that decreased households' agricultural income in recent years: distorted domestic rice prices and deteriorated transport infrastructure. Farmers, especially poor people, are shouldering significant costs and times to transport their produce to markets (**Figures 4 and 5**). The current paper considers three types of transport connectivity for *Z*: (i) proximity to the official road network (denoted by *KM*), (ii) market access index (*MAI*), and (iii) agrobusiness accessibility index (*AGAI*). The last is also disaggregated into two cases: proximity to input- and output-oriented agrobusinesses, denoted by AGAI_i and AGAI_o, respectively.

Figure 4. Average transport costs (US$/50kg bag)



Source: World Bank (2016)

Figure 5. Average transport time (hours)



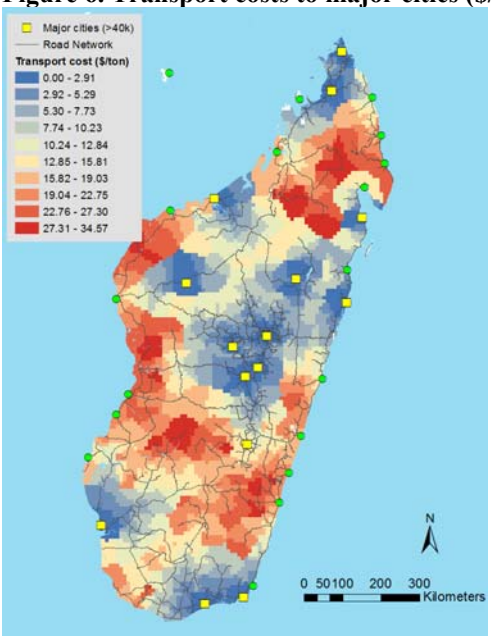
Source: World Bank (2016)

To account for not only transport connectivity but also significance of economic density at each relevant location, the accessibility indices are defined as follows:

$$MAI_i = (\sum_k m_k / d_{ik}) / \max_i MAI_i \qquad (2)$$

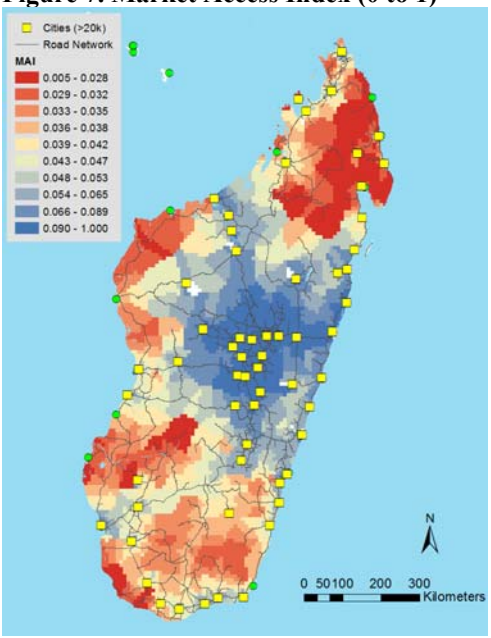
This is the sum of purchasing power or market capacity, *m*, inversely weighted by the degree of impediment (*d*) between two locations.[3] For *m*, the city population is used as a proxy of the market capacity. *d* is measured by estimating transportation costs from pixel *i* and large city *k*.[4] Given the georeferenced road condition data, transport costs to bring one unit of goods to a major market are calculated by spatial software minimizing the total road user costs. In principle, the costs would likely be higher when the road distance is longer and the condition is poor. For instance, **Figure 6** shows estimated transport costs from each SPAM pixel to the nearest major city (with more than 40,000 population). Then, the index is normalized to zero to one.

Figure 6. Transport costs to major cities ($/ton)



Source: World Bank estimate.

Figure 7. Market Access Index (0 to 1)



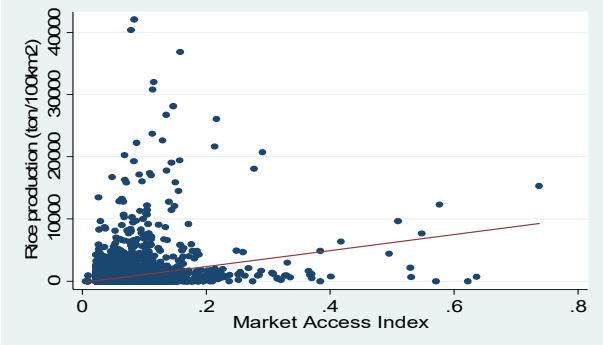
Source: World Bank estimate.

The MAI clearly shows that in Madagascar, the north and the south are disconnected to the primary domestic market, Antananarivo, which is important for everyone (**Figure 7**). In addition, the primary national roads, such as RN2, RN4, RN6 and RN7, are critical to connect those disconnected areas to Antananarivo. Not surprisingly, rice productivity is

[3] This is based on a conventional gravity framework. The literature also uses the negative exponential weights. See for instance Elbadawi, Mengistae and Zeufack (2006) and Lall and Mengistae (2005).
[4] In this paper, 60 cities and towns that have more than 20,000 population are considered.

highly correlated with MAI even in a simple correlation diagram (**Figure 8**). Of course, there is considerable variation, which needs to be controlled by other factors.

Figure 8. Correlation between rice production and MAI



Source: World Bank estimate.

The AGAI is defined in the same way, with the market capacity replaced with the number of agrobusinesses, *s*, that exist in each location (commune). *d* is measured by estimating transportation costs from pixel *i* and location *h*.

$$AGAI_i = (\sum_h s_h/d_{ih})/\max_i AGAI_i \qquad (3)$$

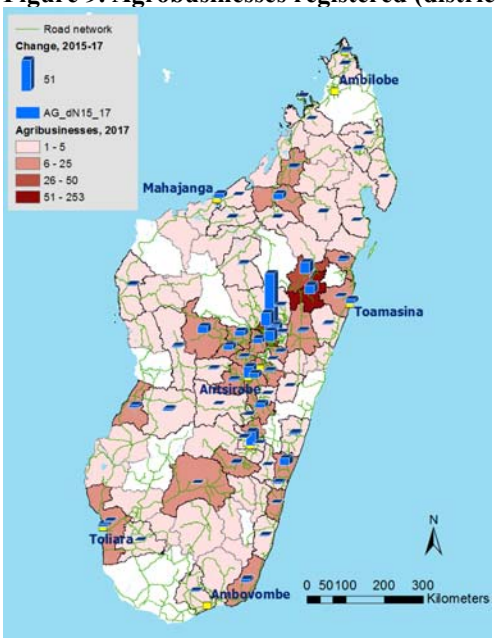
According to the official firm registry database, as of 2017, there existed 1,309 agrobusinesses in the country. Output-related agrobusinesses, including large plantations, collectors, processing companies, and exporters, are dominant, which amount to 902 companies in the database. On the other hand, 399 input-related agrobusinesses, also exist, such as fertilizer and other input dealers and equipment suppliers.[5] The spatial distribution of agrobusinesses is highly skewed (**Figure 9**). 569 firms or nearly half of the total agrobusinesses are located in three districts: Antananarivo, Fianarantsoa and Ambatondrazaka. While the first two are the largest two urban areas in the middle of the

[5] This classification may be ambiguous. In the database, each agrobusiness is categorized as either an input- or output-related firm based on the description of its primary business activity. In practice, however, some of them are likely to engage in both activities.

country, the last is the largest rice production area located between Antananarivo and Toamasina, the primary port city.

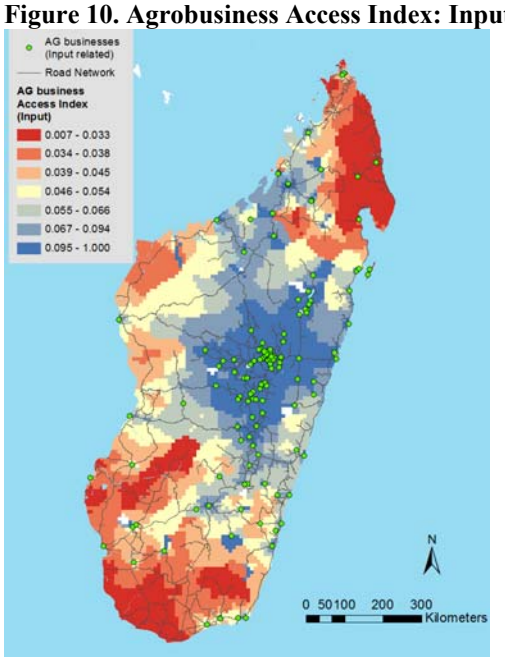
Because of the highly skewed distribution of agrobusinesses, the AGAI is also significantly high around the capital city, Antananarivo. However, there are some local areas which are far from the major cities but have a few agrobusinesses. Since the locational distributions are quite similar between input- and output-oriented agrobusinesses, *AGAI_i* (**Figure 10**) and *AGAI_o* (**Figure 11**) look broadly similar but are not the same, which empirically allows us to examine the potentially different impacts of agrobusiness proximity on rice production.

Figure 9. Agrobusinesses registered (district level)



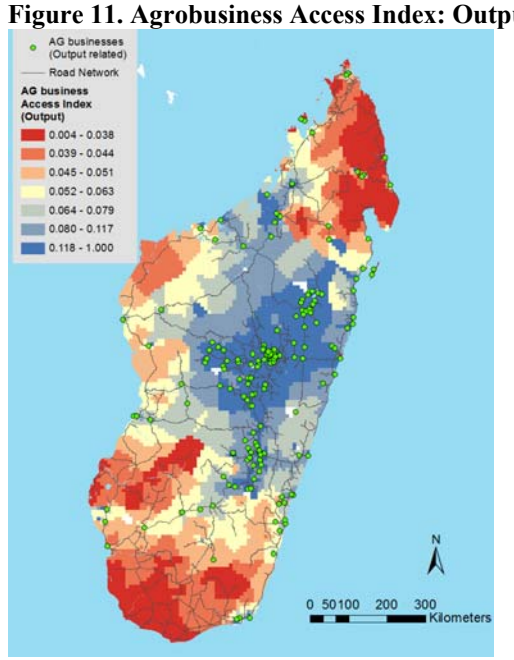
Source: Madagascar Statistical Institute.

Figure 10. Agrobusiness Access Index: Input



Source: World Bank estimate.

Figure 11. Agrobusiness Access Index: Output



Source: World Bank estimate.

To estimate Equation (1), there are several empirical issues. First, there is potential autocorrelation in the error term u. Our primary source of data is the SPAM, which generates spatial data at the approximately10 x 10 km land area level. Thus, even if the difference variables are taken, it is critical to deal with the possible spatial autocorrelation, i.e., $Cov(\Delta u_i, \Delta u_j) \neq 0$. By nature, agricultural land is a continuum of various characteristics, such as soil fertility and water availability. Weather conditions are continuous across near locations. Public infrastructure, such as railway and roads, typically forms a network, which also creates autocorrelation among neighboring areas.

To deal with this problem, the spatial autocorrelation structure is taken into account:

$$\ln Y_i = \lambda \sum_j w_{ij} \ln Y_j + \beta_0 + \beta_A \ln A_i + \sum_k \beta_k \ln X_{ki} + \sum_h \gamma_h \ln Z_{hi} + \rho \sum_j w_{ij} u_j + \varepsilon_i \qquad (4)$$

where w is an element of the spatial-weighting matrix. λ and ρ are spatial autoregressive parameters in the dependent variable and error term, respectively. ε is an idiosyncratic error distributed independently and identically. Under the normality assumption, this can be estimated by the maximum likelihood estimation procedure (e.g., Anselin, 1988; Amaral and Anselin, 2011).[6]

For the spatial weighting matrix, inverse distances between two locations i and j are used. The distance is calculated using the Euclidean distance between the two locations. The intuition is that two locations are more closely related to each other, if they are located closely. This follows Tobler's first law of geography: "everything is related to everything else, but near things are more related than distant things (Tobler 1970)."

Second, as often discussed in agricultural economics, many input variables are often zero in developing countries. A traditional approach is to add a small positive number to avoid taking the logarithm of zeros. This is an accepted practice, however, it may cause a significant bias. Particularly, in our case, no input is used in the vast majority of locations. Thus, Battese's (1997) specification is incorporated in Equation (4):

$$\sum_k \beta_k \ln X_{ki} = \sum_k \beta_k \ln X_{ki}^* + \sum_k \delta_k D_{ki} \qquad (5)$$

where $D_{ki} = \begin{cases} 1 & \text{if } X_{ki} = 0 \\ 0 & \text{if } X_{ki} > 0 \end{cases}$ and $X_{ki}^* = \max(X_{ki}, D_{ki})$.

The summary statistics are shown in **Table 1**.

[6] For estimation we applied a STATA command ***spreg*** developed by Drukker, Prucha and Raciborski (2013).

Table 1. Summary statistics

Variable	Abb.	Obs	Mean	Std. Dev.	Min	Max
Rice produced (ton)	*Q*	3,198	1161.2	3472.4	0.09	120197
Agro-climatic rice productivity (kg/ha)	*A*	3,198	691.6	415.3	0.10	2016
Population who engage in agricultural activities	*L*	3,198	2756.7	6251.8	55.49	210146
Rain-fed land area harvested (ha)	*R*	1,039	179.3	227.7	0.10	1052
Irrigated land area harvested (ha)	*I*	2,527	411.9	565.2	0.90	4908
Fertilizer used (kg)	*F*	3,127	1591.6	2372.3	0.45	22084
Distance to the road network (km)	*KM*	3,198	10.4	9.9	0.00	62
Market Access Index (0 to 1)	*MAI*	3,198	0.061	0.055	0.01	1
Agrobusiness Access Index (0 to 1)						
All agrobusinesses	*AGAI*	3,198	0.085	0.076	0.01	1
Input dealers and suppliers	*AGAI_i*	3,198	0.076	0.077	0.01	1
Output collectors, processing firms, exporters	*AGAI_o*	3,198	0.089	0.085	0.01	1

III. Estimation Results and Policy Implications

First of all, the ordinary least squares (OLS) regression is performed as a basis for discussion (**Table 2**). As discussed above, the results may be biased because of possible autocorrelation in spatial data and excessive zeros in input variables. A small positive number is here used for *R*, *I* and *F* in case they are zero. The results are broadly consistent with economic theory: All inputs are productive. While disconnectedness from the road network has a negative effect, proximity to the market and agrobusinesses look important to increase rice production. Though, one unexpected result is that crop suitability, *A*, has a negative elasticity. It means that farmers might be growing crops in less fertile land, which is not realistic in general.

With the Battese's specification used, the results are broadly similar to the above (**Table 3**). However, the coefficients of some production inputs have been changed, especially for rainfed land, *R*, which has a number of zeros in our data. The coefficients of irrigation *I* and fertilizer *F* also became greater than before, indicating the possible downward bias caused by the small positive number specification. In any case, the OLS estimates are potentially biased without spatial autocorrelation controlled.

Table 2. OLS regression results with the small positive number specification

	OLS			OLS			OLS		
	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
ln*A*	-0.029	(0.014)	**	-0.032	(0.014)	**	-0.034	(0.014)	**
ln*L*	0.305	(0.026)	***	0.354	(0.025)	***	0.344	(0.025)	***
ln*R*	0.099	(0.010)	***	0.099	(0.010)	***	0.100	(0.010)	***
ln*I*	0.142	(0.012)	***	0.150	(0.012)	***	0.148	(0.012)	***
ln*F*	0.482	(0.020)	***	0.471	(0.020)	***	0.473	(0.020)	***
ln*KM*	-0.046	(0.014)	***	-0.069	(0.014)	***	-0.067	(0.014)	***
ln*MAI*	0.583	(0.038)	***						
ln*AGAI*				0.417	(0.032)	***			
ln*AGAI_i*							0.210	(0.063)	***
ln*AGAI_o*							0.248	(0.061)	***
constant	1.948	(0.299)	***	1.075	(0.277)	***	1.273	(0.280)	***
Obs	3,198			3,198			3,198		
F statistic	742.2			724.4			644.87		
R-squared	0.703			0.696			0.698		

Note: The dependent variable is ln*Y*. Robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level, respectively.

Table 3. OLS regression results with the Battese's specification

	OLS			OLS			OLS		
	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
ln*A*	-0.039	(0.015)	***	-0.043	(0.015)	***	-0.044	(0.015)	***
ln*L*	0.289	(0.026)	***	0.334	(0.025)	***	0.325	(0.025)	***
ln*R*	-0.013	(0.030)		-0.034	(0.030)		-0.026	(0.030)	
ln*I*	0.307	(0.033)	***	0.310	(0.034)	***	0.311	(0.034)	***
ln*F*	0.534	(0.031)	***	0.531	(0.032)	***	0.529	(0.032)	***
ln*KM*	-0.053	(0.013)	***	-0.074	(0.013)	***	-0.071	(0.013)	***
ln*MAI*	0.500	(0.038)	***						
ln*AGAI*				0.344	(0.030)	***			
ln*AGAI_i*							0.206	(0.056)	***
ln*AGAI_o*							0.174	(0.053)	***
d*R*	-0.455	(0.107)	***	-0.544	(0.109)	***	-0.517	(0.109)	***
d*I*	1.035	(0.116)	***	1.027	(0.118)	***	1.032	(0.119)	***
d*F*	-0.087	(0.218)		-0.102	(0.225)		-0.104	(0.224)	
constant	0.884	(0.290)	***	0.133	(0.272)		0.294	(0.275)	
Obs	3,198			3,198			3,198		
F statistic	801.6			803.5			736.96		
R-squared	0.738			0.733			0.734		

Note: The dependent variable is ln*Y*. Robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level, respectively.

With spatial autocorrelation taken into account, the spatial autoregressive model is estimated. Again, the model is estimated with both small positive number specification (**Table 4**) and Battese's specification (**Table 5**). The results are broadly similar; however, the latter is our preferred specification for the reasons mentioned above. First, the land potential variable, *A*, now has a small but positive coefficient, which is consistent with our expectation: Farmers are generally cultivating relatively fertile land areas from the agro-climatic perspective.

Second, advanced inputs, such as irrigation and fertilizer, are productive. The elasticities are estimated at about 0.3 and 0.5, respectively. Thus, fertilizer use is important to increase productivity of rice production. On the other hand, the coefficient of labor is still positive but small, indicating that the marginal productivity impact of labor is limited. These are consistent with the view that labor is abundant in rural Madagascar, and further intensification is needed.

Regarding transport connectivity, as expected, proximity to the road network is found to be important. The coefficient of *KM* is consistently negative: The more distant are the areas, the less is production. Note that even though a farming area is not connected to the official road network, there are at least unofficial roads connecting it to the official network. They have not been unclassified yet and are likely to be in very poor condition, because there is no one who is officially responsible for those roads. Madagascar has a low road density of 5.4 km per 100 km^2 (c.f., 8.6 km in Ethiopia and 10.6 km in Tanzania). The estimation result confirms that this last-mile distance is still a constraint on rice production in the country.

Market accessibility is also important. The coefficient of *MAI* is estimated at 0.31, which is statistically significant and numerically relatively large. A policy implication is that transport infrastructure connecting farmers and major markets, especially the capital city, Antananarivo, is important to be developed and maintained. Without improving access to Antananarivo, agricultural growth cannot be stimulated.

The estimation results show that proximity to agrobusinesses has a positive impact on rice production: The elasticity with respect to AGAI is 0.16. When disaggregating into input- and output-oriented firms, this impact is mainly explained by the effect of input-oriented agrobusinesses. While *AGAI_i* has a positive and significant coefficient of 0.22, the coefficient of *AGAI_o* is negative and insignificant. This is consistent with the above finding that the advanced input variables, fertilizer and irrigation, have large elasticities. It can be interpreted to mean that input-related agrobusinesses, such as input dealers and equipment suppliers, are important to stimulate rice production further in Madagascar. Since they are mainly located to major urban areas, transport infrastructure is critical to connect them to local farmers.

Of course, the possible impact of output-oriented agrobusinesses may have been captured by market accessibility (*MAI*) to a certain extent. When all accessibility indices are included, the impact of MAI dominates all other effects. However, the relative importance of input-related agrobusinesses remains unchanged. Therefore, it can be concluded that in Madagascar, access to input-related agricultural services is more critical for rice production growth.

Table 4. Spatial autoregressive model with the small positive number specification

	Spatial regression			Spatial regression			Spatial regression		
	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
ln*A*	0.038	(0.011)	***	0.047	(0.011)	***	0.045	(0.011)	***
ln*L*	0.097	(0.020)	***	0.094	(0.020)	***	0.095	(0.020)	***
ln*R*	0.100	(0.009)	***	0.101	(0.009)	***	0.101	(0.009)	***
ln*I*	0.133	(0.010)	***	0.136	(0.010)	***	0.136	(0.010)	***
ln*F*	0.518	(0.011)	***	0.511	(0.011)	***	0.512	(0.011)	***
ln*KM*	-0.055	(0.011)	***	-0.065	(0.011)	***	-0.064	(0.011)	***
ln*MAI*	0.247	(0.028)	***						
ln*AGAI*				0.144	(0.025)	***			
ln*AGAI_i*							0.172	(0.051)	***
ln*AGAI_o*							-0.012	(0.051)	
constant	-7.090	(0.393)	***	-7.992	(0.348)	***	-7.920	(0.357)	***
Obs	3,198			3,198			3,198		
Wald chi2	7343.2			7263.4			7288.1		
Spatial parameters:									
λ	1.554	(0.056)		1.652	(0.047)		1.650	(0.049)	

ρ	5.331			5.317	(0.100)		5.319	(0.075)	

Note: The dependent variable is ln*Y*. Robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level, respectively.

Table 5. Spatial autoregressive model with the Battese's specification

	Spatial regression			Spatial regression			Spatial regression		
	Coef.	Std.Err.		Coef.	Std.Err.		Coef.	Std.Err.	
ln*A*	0.030	(0.010)	***	0.048	(0.010)	***	0.045	(0.010)	***
ln*L*	0.040	(0.018)	**	0.048	(0.019)	**	0.044	(0.019)	**
ln*R*	0.167	(0.020)	***	0.157	(0.020)	***	0.161	(0.020)	***
ln*I*	0.316	(0.024)	***	0.311	(0.024)	***	0.313	(0.024)	***
ln*F*	0.527	(0.022)	***	0.525	(0.023)	***	0.523	(0.023)	***
ln*KM*	-0.053	(0.010)	***	-0.062	(0.010)	***	-0.061	(0.010)	***
ln*MAI*	0.310	(0.024)	***						
ln*AGAI*				0.166	(0.024)	***			
ln*AGAI_i*							0.224	(0.046)	***
ln*AGAI_o*							-0.041	(0.048)	
d*R*	0.268	(0.085)	***	0.260	(0.088)	***	0.266	(0.087)	***
d*I*	1.056	(0.092)	***	1.022	(0.093)	***	1.031	(0.093)	***
d*F*	0.073	(0.114)		0.117	(0.116)		0.103	(0.116)	
constant	-6.719	(0.362)	***	-8.243	(0.387)	***	-8.168	(0.390)	***
Obs	3,198			3,198			3,198		
Wald chi2	9426.3			9189.5			9230.7		
Spatial parameters:									
λ	1.332	(0.051)		1.497	(0.056)		1.503	(0.056)	
ρ	5.963	(0.087)		5.404	(0.122)		5.540	(0.046)	

Note: The dependent variable is ln*Y*. Robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level, respectively.

IV. CONCLUSION

In the literature, there are a number of empirical studies showing a wide range of impacts of improved transport connectivity on agricultural growth. Still, the assumed nexus between transport infrastructure and agricultural growth remains somewhat mysterious, particularly in the African context. One of the missing important elements is agrobusiness. Because many rural farmers do not have their own transport means, someone has to deliver advanced inputs, and go and pick up their produce. Agrobusinesses, such as input suppliers, collectors, processors and exporters, have a crucial role to play in this regard.

The paper reexamined such a nexus among crop production, transport infrastructure and agrobusinesses. The results show the particular importance of intensification in Malagasy rice production. Fertilizer use has the highest elasticity, followed by irrigation and market accessibility. Consistently, the results indicate the importance of agrobusinesses. Particularly, proximity to input-oriented agrobusinesses, such as input dealers and equipment suppliers, is found to be important: They can facilitate farmers' adoption of new inputs and technologies.

Methodologically, the paper also attempted to apply newly available data and techniques. Spatial data are generally rich data sources, which allow to generate various information that would be unavailable or very costly to collect otherwise. The paper combined highly disaggregated crop production data and detailed geo-referenced road network data. Various transport accessibility measurements were developed, which are clearly useful to consider many other policy issues.

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